COMPARISON BETWEEN DIFFERENT VERSIONS OF INPE'S FIRE RISK MODEL FOR THE BRAZILIAN BIOMES

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ABSTRACT:

Fires are intrinsic disturbances in ecosystems functioning and structure in fire-prone biomes. In recent decades there has been an increase in the number of fire events in Brazilian biomes, especially due to misuse of fire in the land use and deforestation. The spatial and temporal pattern fire risk is a important way to understanding the seasonality and intensity of fire in different climate and fuel conditions. However, consistent long-term assessment at biome level is only possible with the support of remote sensing and modeling information. Thus, the objective of this work was to evaluate the fire risk patterns for the Brazilian biomes in the last years (2015-2018), using the new version of INPE's fire risk (FR, v2). Regarding the temporal and spatial FR patterns by this new version from FR model, we evaluated that elevation and latitude correction factors, as well as the meteorological and land cover datasets with finer spatial scales can be contributed to adjust better the fire season vulnerability, notably in the less prone-biomes, such as Mata Atlantica, Pampa and Pantanal. However, there is still a need for adjustment to match the spatial active fire distribution, considering a biomass (fuel) map and the vegetation water status indicators. These improvements help to inform with more accuracy the most fire prone areas to define the strategies and decisions for fire combat and management.

1. INTRODUCTION

Fire is an important component in biosphere-atmosphere interactions due to changes in atmosphere composition, greenhouse gas emissions and the influence on the structure and functioning of various ecosystems (Bond., 2008). In recent decades there has been an increase in the number of active outbreaks and burned areas in Brazilian biomes (INPE, 2019), especially due to the use of fire as a soil management tool, the opening of new agricultural land, deforestation, pasture renewal (Araujo et al., 2012) and due to extreme weather conditions (Aragão et al., 2018). However, the inappropriate use of fire has altered its regime, causing enormous socioeconomic and environmental damages.

In this regard, an assessment of the potential fire risk on threatened land is a way for making fire combat and management measures and decisions to obtain as little damage as possible. For this, it is essential to understand the historical dynamics of fire risk in these areas. However, consistent long-term assessment at biome level is only possible with the support of remote sensing and modeling information. This information allows repetitive integration of satellite data under the same location for time series extraction at this spatial scale level.

Moreover, many factors influence the fire behavior and its spread, such as topography, terrain slope, weather factors (precipitation, wind, temperature and relative humidity), vegetation type and extreme weather events. Altitude variation alters fire behavior by interfering with wind displacement, precipitation distribution and vegetation types (Schroeder, Buck, 1970).

Fire risk modeling has become an useful tool in assessing environmental resilience under human intervention situations, as well as in the interaction between deforestation and climate, which can lead differents ecosystems to an irreversible cycle of destruction, as the founded in Brazilian biomes.

Amazonia is a broadleaf tropical rainforest from Amazon basin, presenting the most largest tropical biodiversity in the world (WWF, 2019). Its main feature is the warm and humid climate and dense vegetation types. Cerrado's vegetation is marked by different vegetation stratum, ranging from relatively low trees, shrubs to the predominance of grassland formation (Oliveira-Filho, Ratter, 2002). This biome is co-evolved with fire occurrence, where the most species with mechanisms and strategies adapted to fire (Oliveira-Filho, Ratter, 2002), which occurs in dry seasons. Territory's Mata Atlantica with the occupation and human activities in the last decennies rest about 29% of its original coverage remains. This biome is formed by different vegetation stratum but with predominance of seasonal tropical forests with the one of the most diverse ecosystems on the planet (WWF, 2019). Caatinga is the main biome of the Northeast Region, marked by a vegetation type from semiarid regions, with xerophilous plants adapted to the dry climate and water hydric stress (Costa, 2014). Its has been rapidly deforested, mainly in recent years in about 46% of its territory (MMA, 2019). Pampa has great richness of herbaceous species and presents humid climate with irregular distribution of rainfall, cold fronts and negative temperatures in the winter season. Finally, the Pantanal biome, which represents only 1.76% from Brazil, is present only in two states (Mato Grosso and Mato Grosso do Sul). Its main feature is the long-term floods that occur annually, providing a very diverse and unique fauna (Costa, 2014).

Thus, the objective of this work was to evaluate the fire risk patterns in Brazilian biomes in the last four years (2015-2018), using the new version of INPE's fire risk (v2) model, to understand the areas most vulnerable to burning.

2. METHODOLOGY

2.1. Study area

Brazil is located at 73.98°W − 33.87°W/longitude and 28.63°S − 5.28°N/latitude in the South America, with 8.511.000 km² of spatial extension. The main Brazilian ecosystems are divided in six biomes: Amazonia, Cerrado, Caatinga, Mata Atlantica, Pampa and Pantanal (Figure 1).

The Amazonia biome is the largest biome (49.29%) in Brazil (IBGE, 2019), present in the Northern region of the country. The Cerrado is the second largest biome (22.00%) with an distribution in different Brazilian regions with the largest predominance in the Central-Midwest region. Atlantic Forest and Caatinga occupies, respectively 13.04% and 11.00% of the national territory. Whereas the Pampa (2.07% of Brazil) is present only in the Rio Grande do Sul state, in the Southern part.

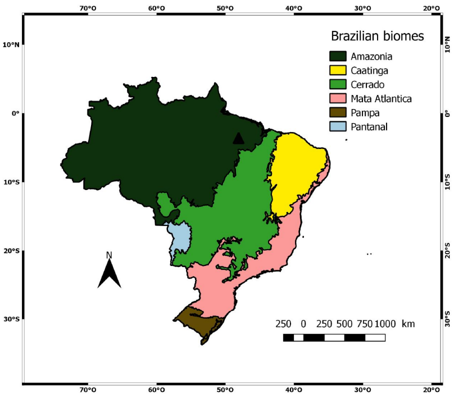

Figure 1. Spatial distribution of Brazilian biomes.

2.2. Fire Risk model

The Fire Risk (FR) used in this paper is based on the local fuel type of the predominant land cover (LC) in each pixel from Latin America. FR indicates how favorable the vegetation can be burned, regarding the meteorological conditions and considering that the most fire occurrences in Brazil are initiated by humans and not naturally (i.e.lightning) (Setzer et al., 2019). The FR model is a product from INPE's Forest Burn and Fire Monitoring Program (http.://www.inpe.br/queimadas), developed at the Center for Weather Forecasting and Climate Studies/National Institute for Space Research (CPTEC/INPE), with its pioneer version (version 0) operational since 1999 until 2018.

FR from v0 is based on dry days (PSE), the rainfall of the last 120 days, combined with air temperature (T) and relative humidity (UR) information, both at the surface. The predominant LC are evaluated in seven classes, according to the classification of the Brazilian Institute of Geography and Statistics (IBGE). In each LC classe is associated a flammability constant ("A"), according to Table 1.

Table 1. The seven land cover (LC) classes and its respective flammability constant ("A") used in the INPE's Fire Risk model

	LC	A
0	Water, sandy	-
1	Grasslands	2.0
2	Cropland and Cropland/Natural vegetation mosaic	1.5
3	Open shrublands/Savannas	2.0
4	Closed shrublands/Woody savannas	1.72
5	Evergreen Needleleaf Forests	2.0
6	Deciduous Needleleaf/ Mixed Forests	2.4
7	Evergreen Broadleaf Forests/Permanent wetlands	3.0

v0 is generated on the daily scale using the accumulated P for eleven periods (1; 2; 3; 4; 5; 6 to 10; 11 to 15; 16 to 30; 31 to 60; 61 to 90; and 91 to 120 last days). Subsequently, the "precipitation factors" are calculated, whose values range from 0 to 1 for the 11 periods above, using an empirical exponential precipitation function for each period. Then the PSE values are defined as the number of days without any precipitation during the last 120 days from the date of interest. Thus, once the PSE is obtained, the basic potential basic fire risk (RB) is determined in according to the equation below:

$$RB = \frac{0,8 \times \{1 + sin[(A \times PSE) - 90]\}}{2} \quad (1)$$

where RB is a basic potential fire risk, varying between 0 and 1; PSE is the number of days without any precipitation during the last 120 days from the date of interest (mm day^{-1}) and "A" is the flammability constant that depends on the predominant land cover type, in according to Table 1.

The UR (FU) and T (FT) factors in RF are evaluated in according to equations 2 and 3, respectively . These factors use the minimum RH (RH_{min}, %) and the maximum T (T_{max}, ºC). The risk increases (decreases) for RH_{min} below (above) 40% and T_{max} above (below) 30 °C. Then, the RB is corrected by FU and FT, resulting in the FR0 expressed in equation 4.

$$FU = [RH \times (-0.006)] + 1,3 \quad (2)$$

where RH is relative humidity in %

$$FT = (T \times 0,002) + 0,4 \quad (3)$$

where T is air temperature in °C

$$FR\,(v0) = RB \times FU \times FT \quad (4)$$

where RB is basic fire risk (0-1), FU and FT are relative humidity and temperature factors, respectively

The latest FR version implemented in 2019 (version 2, v2) (Setzer et al., 2019) also considers the elevation (FELV, equation 5) and latitude (FLAT, equation 6) effects in the FR (v0) calculation, resulting in equation 7.

$$FELV = 1 + ELEV \times 0,00003 \quad (5)$$

where ELEV is elevation in meters

$$FLAT = (1 + abs(LAT) \times 0,003) \quad (6)$$

where LAT is latitude in degrees

$$FR\,(v2) = FR\,(v0) \times FLAT \times FELV \quad (7)$$

where FR (v0) is a fire risk in the version 0, FLAT and FELV are elevation and latitude correction factors, respectively.

2.3. Datasets

We used the P (mm.day^{-1}) data derived from two datasets. For the v0 calculation, the P estimates are derived from CoSch dataset (Vila et al., 2009) and from Integrated Multi-satellitE Retrievals for GPM (IMERG, Huffman et al., 2014, 2015) for the v2. The CoSch is a precipitation estimate that combines weather station data with satellite information at 25 km x 25 km of spatial resolution. The IMERG is a combination of surface observed data, satellite images, weather radar and atmospheric models obtained from for Global Precipitation Measurement (GPM) at 10 km x 10 km of spatial resolution. T (°C) and RH (%) data were obtained from the Global Forecast System (GFS) at 25 km x 25 km horizontal resolution, available in https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-forcast-system-gfs. These two variables were obtained at 18 UTC, which corresponds to the time of maximum air temperature and minimum relative humidity.

The effects of topography were evaluated using the elevation (m) information generated by the Shuttle Radar Topography Mission Digital Elevation Model (SRTM, https://lta.cr.usgs.gov/SRTM), available at 1 second arc (~30m) resolution across South America.

The LC classes in v0 are derived from a reclassification from MCD12Q1 v005 (Friedl et al., 2010) product generated by MODIS (Moderate Resolution Imaging Spectroradiometer) sensor, with International Geosphere-Biosphere Program (IGBP) classification (Friedl, M., Sulla-Menashe, D., 2015) at 500m spatial resolution. In v2, we used a reclassification of LC spatial distribution derived from MapBiomas v3.1 (http://mapbiomas.org) dataset, whose data are generated by Landsat sensor at 30 m spatial resolution. All climate, topography and LC maps were interpolated and evaluated at 1km of spatial resolution.

2.4. Data analysis

We compared the version v0 and v2 using the average monthly of fire risk (FR) from 2015 to 2018. FR were quantified in each pixel of Brazilian biomes and evaluated according to five categories**:** 1-minimum ($FR \leq 0.15$), 2-low ($0.15<FR \leq 0.4$), 3-medium ($0.4<FR \leq 0.70$), 4-high ($0.70<FR \leq 0.95$) and 5-critical ($FR>0.95$). These different versions were compared with the mean of total active fire number for the same period, detected by reference satellite AQUA-MODIS used in the INPE's BDQueimadas (www.inpe.br/queimadas/bdqueimadas) and considered here as reference for the temporal distribution of fire occurrence in each biome.

3. RESULTS AND DISCUSSION

3.1. Temporal FR patterns

The Brazilian biomes showed different temporal FR patterns distributions from 2015 to 2018 in the both versions (v0 and v2) (Figure 1). Caatinga, Cerrado and Pantanal showed more months susceptible to fire, with medium to high FR and concentrated in the months of dry season (DS, May to November, May to October and April to September, respectively) (Figure 1b, c and f).

The highest active fires values (HAF) in theses biomes were observed in October for Caatinga (Figure 1b) and in September for Cerrado and Pantanal (Figure 1c-d). While as the highest FR values (critical FR) were observed in from July to October in Caatinga and in July for Cerrado and Pantanal, all from both versions.

The minimum and low FR classes were observed in Amazonia and Pampas with maximum values in August and June, respectively, from both versions (Figure 1a, e). However, the HAF in Amazonia and Pantanal was observed in September. In Mata Atlantica was observed a medium-high FR from April to October from both versions, with HAF in the September and the highest FR value in July (Figure 1d).

In the Amazonia, Caatinga, Cerrado and Mata Atlantica (Figure 1 a-d), the v0 and v2 not showed differences, whileas Pampa had predominantly minimum FR by v0 versus low FR by v2 (Figure 1e). The main temporal patterns differences between v0 and v2 were observed in the Pantanal, with FR from low-medium by v0 and FR from low-high by v2 (Figure 1f). The FR distribution in Pantanal is similar by both versions, however, v2 showed a high FR since June whileas for v0, this month had a medium FR in this month.

Regarding the temporal FR patterns, we verified that the modifications in v2 can contribute to adjust better the fire season vulnerability, especially in the less prone-biomes, such as Mata Atlantica, Pampa and Pantanal. However, the temporal distribution is not coincident with the active fires, what requires most improvements in the current INPE's fire risk model.

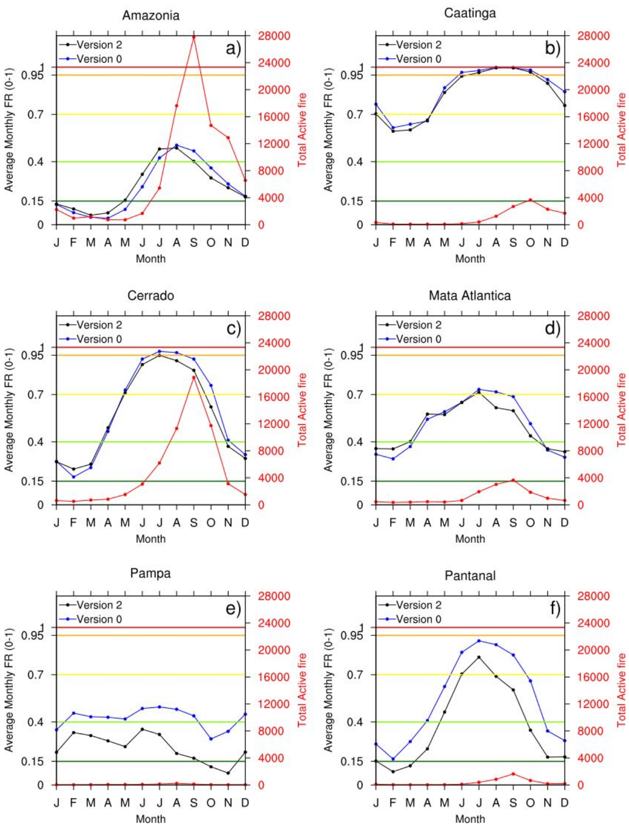

Figure 2. Monthly average Fire Risk (FR) in Brazilian biomes from version 0 (blue) and 2 (black) of INPE's fire risk model compared to mean total active fires (red) for the 2015-2018 period. FR is expressed in five classes, represented in continuous lines: minimum ($FR \leq 0.15$, dark green), low ($0.15<FR \leq 0.4$, light green), medium ($0.4<FR \leq 0.70$, yellow), high ($0.70<FR \leq 0.95$, orange) and critical ($FR>0.95$, red)

3.2. Spatial FR patterns

The figure 3 demonstrates the spatial FR distribution in each Brazilian biome in the months with highest active fires (HAF), whose spatial distribution also are showed in the Figure 1, Appendix).

In Amazonia, critical FR had a spatial distribution by v2 more coherent with the HAF distribution in August, in the Southeast's part of this biome (Figure 3a), the Arc of deforestation, where the most fire occurrences are concentrated in Amazonia (Fanin, van der Werf, 2015).

In Pampas, the spatial distribution of FR is different between versions, with predominantly low FR by v2 and high FR by v0 (Figure 3b). In this case, v2 represents better the fire occurrences distribution because June is the driest month in Rio Grande do Sul state (Reboita et al., 2010), reducing the FR.

The same coherence between FR and HAF was observed in Pantanal high (low) FR and HAF in the (west) east part of this biome (Figure 3c).

The spatial FR distribution in the Mata Atlantica and Caatinga biomes are not very different (Figure 3d, f). The main differences are observed in the ecoton region between these biomes (Center-North of Mata Atlantica), where the FR is modified to predominantly high-critical in v2.

Finally, Cerrado had predominantly high to critical FR from the center to north (Figure 3e) in September, coherent with other findings in Cerrado (Rodrigues et al., 2019) and especially in the part of the newest agricultural frontier from Cerrado biome (MATOPIBA), where the fire is yet used as tool to land management (Miranda et al., 2014).

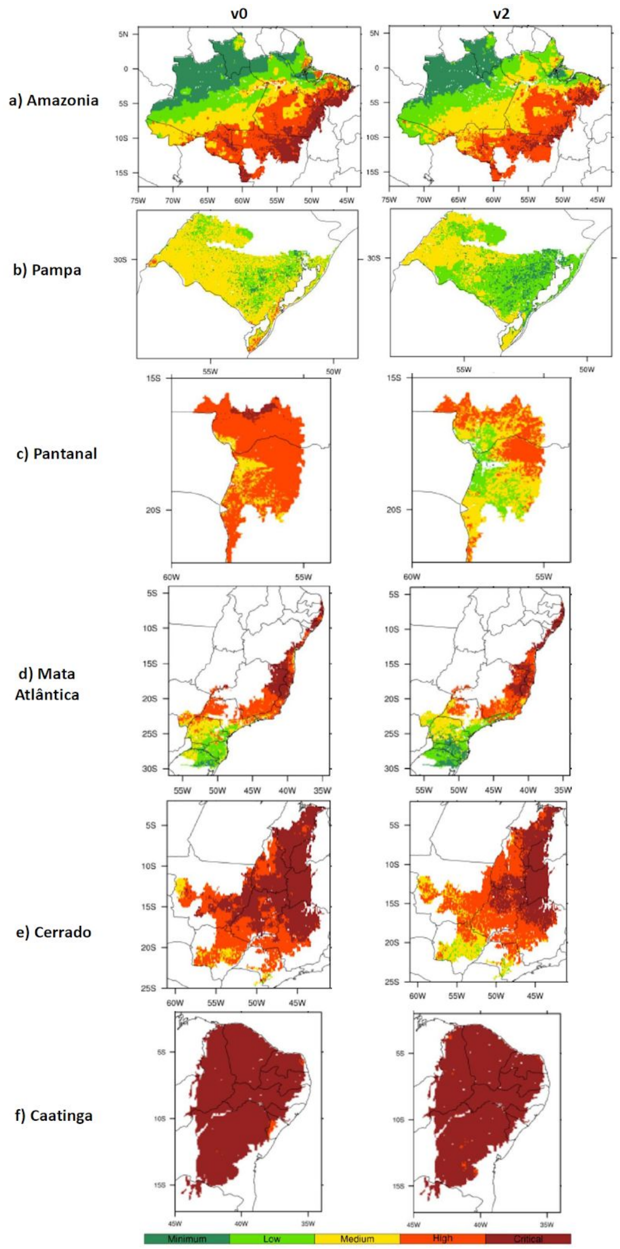

Figure 3. Spatial distribution of average monthly fire risk in the months with the highest fire actives in each Brazilian biome: August (Amazonia), June (Pampas), Cerrado, Pantanal and Mata Atlantica (September), Caatinga (October), from version 0 (left) and 2 (right) of INPE's fire risk model, in the period of 2015-2018 period. FR is expressed in five classes: minimum ($FR \leq 0.15$, dark green), low ($0.15<FR \leq 0.4$, light green), medium ($0.4<FR \leq 0.70$, yellow), high ($0.70<FR \leq 0.95$, orange) and critical ($FR>0.95$, red)

4. CONCLUSION

Regarding the temporal and spatial FR patterns by this new version from FR model, we verified that elevation and latitude correction factors, as well as the meteorological and land cover datasets with finer spatial scales contributed to adjust better the fire season vulnerability, especially in the less prone-biomes, such as Mata Atlantica, Pampa and Pantanal.

INPE's fire risk model have been showed a useful tool to identify regions that are favorable for the meteorological fire risk, i.e, it does not considers the wind (direction and speed) effects that would be associated with the fire spread. However, there is still a need for adjustment to match the spatial active fire distribution as shown in the results. A more refined biomass (fuel) map and the vegetation water status indicators can contribute to refine the INPE's FR model. These improvements help to inform with more accuracy the most fire prone areas to define the strategies and decisions for fire combat and management.

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REFERENCES

Aragão, L.E.O.C., Anderson, L.O., Fonseca, M.G., Rosan, T.M., Vedovato, L.B., Wagner, F.H., Silva, C.V.J., Silva Junior, C.H.L., Arai, E., Aguiar, A.P., Barlow, J., Berenguer, E., Deeter, Domingues, L.G., Gatti, L., Gloor, M., Malhi, Y., Marengo, J.A., J.B.M, Oliver., 2018: 21st Century drought-related fires counteract the decline of Amazon deforestation carbon emissions. *Nature Communications*. 9, 536. doi:10.1038/s41467-017-02771-y.

Araújo, F.M., Ferreira, L.G., Arantes, A.E., 2012: Distribution Patterns of Burned Areas in the Brazilian Biomes: An Analysis Based on Satellite Data for the 2002–2010 Period. *Remote Sensing*, 4, 1929-1946.

Bond, W.J., 2008: What Limits Trees in C_4 Grasslands and Savannas? *Annual Review of Ecology, Evolution, and Systematics*, 39 (1), 641–659.

Costa, S.L.L. Correlações de longo alcance em séries temporais de focos de calor nos biomas brasileiros. 2014. 56 f. Dissertação (Programa de Pós-Graduação em Biometria e Estatística Aplicada) - Universidade Federal Rural de Pernambuco, Recife.

Fanin, T., van der Werf, G.R., 2015: Relationships between burned area, forest cover loss, and land cover change in the Brazilian Amazon based on satellite data, 12, 6033–6043.

Friedl, D.M.A., Sulla-Menashe, B. Tan, A. Schneider, N. Ramankutty, A. Sibley, X. Huang., 2010. MODIS Collection 5 global land cover: algorithm refinements and characterization of new datasets. *Remote Sensing of Environment*, 114 (1), 168–.

Friedl, M., Sulla-Menashe, D., 2015. MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006. NASA EOSDIS Land Processes DAAC. doi: 10.5067/MODIS/MCD12Q1.006.

Huffman G.J., Bolvin, D.T., Braithwaite, D., Hsu, K., Joyce, R., Xie, P., 2014. GPM Integrated Multi-Satellite Retrievals for GPM (IMERG) Algorithm Theoretical Basis Document (ATBD) Version 4.5. Greenbelt, MD, 30 p.

Huffman G.J., Bolvin, D.T., Nelkin, E.J., 2015. Integrated Multi-satellitE Retrievals for GPM (IMERG) technical documentation. NASA Doc., 47 p.

IBGE. Instituto Brasileiro de Geografia e Estatística. 2019. Available at: <https://www.ibge.gov.br>.

INPE. Instituto Nacional de Pesquisas Espaciais. 2019. Available at: <http://www.inpe.br>.

MapBiomas Project, 2019. Collection 3.1 of Brazil's Annual Land cover and Land Use Mapping. Available at <https://mapbiomas.org>.

Miranda, E.E., Magalhães, L.A., Carvalho, C.A. Proposta de delimitação territorial do MATOPIBA. *Nota Técnica 1*, GITE – Grupo de Inteligência Territorial Estratégica, Embrapa, Campinas, SP, maio/2014.

MMA. Ministério do Meio Ambiente. 2019. Available at: <https://www.mma.gov.br/biomas.html>.

Oliveira-Filho, A.T., Ratter, J.A., 2002. Vegetation physiognomies and wood flora of the Cerrado biome. In: Oliveira, P.S. and Marquis, R.J., Eds., The Cerrados of Brazil: Ecology and Natural History of a Neotropical Savanna, Columbia University, New York, 91–120.

Reboita, M.S., Gan, M.A., Rocha, R.P., Ambrizzi, T., 2010: Regimes de Precipitação na América do Sul: Uma revisão bibliográfica, 25, 185–.

Rodrigues, J.A., Libonati, R., Pereira, A.A., Nogueira, J.M.P., Santos, F.L.M., Peres, L.F., Rosa, A.S., Schroeder, W., Pereira, J.M.C., Giglio, L., Trigo, I.F., Setzer, A.W., 2019: How well do global burned area products represent fire patterns in the Brazilian Savannas biome? An accuracy assessment of the MCD64 collections. *International Journal of Applied Earth Observation and Geoinformation* , 78, 318–331.

Schroeder, M.J., Buck, C.C. Fire weather: a guide for application of meteorological information to forest fire control operations. USDA Forest Service, Agriculture Handbook 360, 1970. 229 p.

Setzer, A.W., Sismanoglu, R.A., Santos, J.G.M. Método do cálculo do risco de fogo do programa do INPE - Versão 11, junho/2019. São José dos Campos: INPE (2019). 27 p. IBI: <8JMKD3MGP3W34R/3UEDKUB>. (sid.inpe.br/mtc-m21c/2019/11.21.11.03-PRP). Available in: <http://urlib.net/rep/8JMKD3MGP3W34R/3UEDKUB>.

Vila, D.A., de Gonçalves, L.G.G., Toll, D.L., Rozante, J.R, 2009: Statistical evaluation of combined daily gauge observations and rainfall satellite estimates over continental South America. *Journal of Hydrometeorology*, 10, 533–543.

WWF. World Wide Fund For Nature. 2019. Available at <http://wwf.panda.org>.

APPENDIX

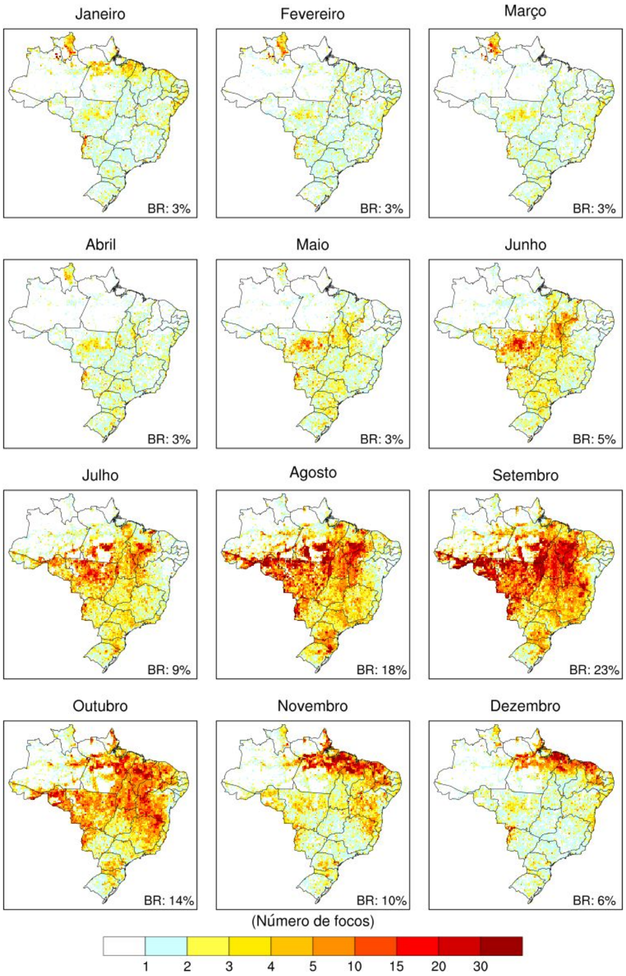

Figure 1. Appendix. Spatial distribution of monthly average active fires in Brazil from 2015 to 2018, detected by the AQUA-MODIS satellite. A percentage in the bottom right represents the monthly contribution to active fire.